Psychophysiological Measures of Cognitive Absorption and Cognitive Load in E-Learning Applications

Research-in-Progress

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Abstract

By understanding the psychophysiological factors behind successful e-learning, we aim to identify new techniques that improve participant retention and engagement. Past work has explored the relationship between Electroencephalography (EEG) and learning constructs, such as Cognitive Load and Cognitive Absorption. We believe that the unique application of an e-learning environment warrants an extension of existing theories. Our goal is to develop and validate a model explaining the role of Cognitive Load on Knowledge Gained. This research provides the foundation to then apply this model to create a neuroadaptive learning system. *We describe an experiment that uses noninvasive tools to validate this model and explore the viability of off-the-shelf EEG for data collection in e-learning experiments. Potential theoretical contributions are discussed and results from a technical pilot are provided.*

Keywords: E-learning, Cognition/cognitive science, Flow, Human-computer interaction

Introduction

E-learning, also known as online learning, has emerged as having enormous potential for customized, on-demand student education and professional development in organizations. A number of recent innovations, such as Massive Open Online Courses (MOOCs) have been noted for their ability to disrupt traditional education by providing scalable access to content created by leading educators (Christensen, et al., 2014). However, much of the initial enthusiasm behind the technology has given way to a degree of skepticism that is fostered in part by low course completion rates and poor student performance (Ho, et al., 2014). Cognitive retention, poor user engagement, a lack of social experience and poor user motivation have been suggested as potential causes of this failure (Chandrasekaran, et al., 2015; Greene, et al., 2015; Reich, 2014). Our goal is to identify and empirically validate a theory explaining social, immersive and engaging online learning behavior, which is essential to improving the online learning experience.

Cognitive Absorption (CA) is a model that has been used to explain experiences that are deeply immersive and enjoyable, under which lasting learning can occur (Agarwal, et al., 2000). Cognitive absorption refers to the psychophysiological mechanisms underpinning successful e-learning experiences using simulations (Léger, et al., 2014; 2010). The CA model is grounded in the theory of psychological flow. When a user is in a state of flow, she has heightened attention and becomes so absorbed in the activity she loses track of time (Csikszentmihalyi, 1990). Users in a state of flow are engaged, intrinsically motivated and are therefore more likely to retain the e-learning material. It follows that we might also measure cognitive absorption using physiological indicators, such as heart rate or brain activity, as demonstrated by Léger, et al. (2014).

However, cognitive absorption appears to conflict with the theory of Cognitive Load (CL). Cognitive load holds that the acquisition learning outcomes are determined by comprehension difficulty, not enjoyment, and that learning performance is negatively affected by high mental workload (Sweller, 1994; Sweller, 1988). If students are confronted with too much information, such as that presented in a realistic simulation, it follows that they would become overwhelmed, and less likely to achieve the learning outcomes. Cognitive absorption hinges on there being sufficiently complex and engaging stimuli. CA thus seems to meet resistance from the theory of cognitive load, which states that too much stimuli impedes learning. If CL impacts learning then it becomes important to explore the relationship between a user's degree of technical expertise and physiological measures such as brain activity or browser behavior. These traits may be indicative of the degree of CL. Understanding this relationship will allow us to measure CL in real-time without relying on self-reported scales. Such a methodology could be instrumental in improving e-learning delivery techniques.

This paper has two goals. The first is to identify an appropriate theory explaining the neurocognitive mechanisms behind e-learning. This goal is achieved by surveying the literature on cognitive absorption and cognitive load, and identifying a theoretical ground for an e-learning model. The second goal is to identify hypotheses and related to measuring successful e-learning and to identify methods for testing these hypotheses using non-invasive tools applicable to online learning. If successful, our findings will help to identify the precise methods for measuring the appropriate degree of challenge in a MOOC e-learning environment. In the following sections, we discuss the relevant literature concerning the apparent theoretical gap between cognitive absorption and cognitive load. We then propose a theoretical framework for validating a cognitive load based model explaining learning. Finally, we discuss preliminary findings from a proof of concept pilot study conducted using electroencephalography (EEG).

Theoretical Background

Our objective in this section is to outline a theoretical framework for testing the impact of conceptual difficulty on the attainment of learning outcomes. It has been widely accepted that both cognitive absorption and cognitive load impact learning attainment and technology acceptance. In the following paragraphs, we explore the commonalities and differences between the two theories, arriving at hypotheses to test related to the impact of task difficulty in triggering cognitive absorption.

Measuring Flow and Cognitive Absorption

Originally proposed by Csikszentmihalyi in the early 1990's, Flow has been an influential concept across Information Systems, Psychology and Learning disciplines. Cognitive Absorption (CA) is a construct used to describe a state of deep involvement with IT, with theoretical roots in the theory of Flow (Agarwal, et al., 2000). Research suggests that CA has a significant impact on IT users' intention to use the target information system (Léger, et al., 2010; 2014; Saadé, et al., 2005; Scott, et al., 2009). Simulations have been used to trigger cognitive absorption since at least the early 2000's, and have been shown to have a dramatic positive impact in the classroom learning environment (Lu, et al., 2014). By drawing users into an engaging e-learning expierience that triggers CA, it is theorized that users will see greater technology acceptance and a higher degree of competency.

Flow was originally conceptualized by Csikszentmihalyi as a state under which individuals engage in an activity for its own sake; in other words, are intrinsically motivated to engage in the activity (Csikszentmihalyi, 1990). Flow activities are *enjoyable* and could include activities such as "play, art, pageantry, ritual and sports," but also include the play of ideas, philosophy and the acquisition of new knowledge (Csikszentmihalyi, 1990). In this respect, flow could be experienced in the conditions that makes learning possible. Flow could also be seen as a sufficient, but not necessary condition of learning under cognitive load theory.

Past work on measuring flow in learning situations could be placed in two categories: *conventional* and *psychophysiological*. Conventional work on flow largely involves the use of psychometric scales to measure participant preceptions (Jackson, et al., 2004; Ullén, et al., 2012). Related to simulation-based e-learning, some psychometric scales have been specifically developed to measure preceived flow in video games (Soutter, et al., 2016; Van Looy, et al., 2012). Attempts have also been made to measure flow for the purposes of e-commerce and online marketing, however the construct was found to be too ellusive to be useful (Hoffman, et al., 2009). A major challenge with convential measures in the context of e-learning is that they cannot be used in real-time when a participant is cognitively absorbed. As Randolph et al. (2015) discuss, psychometric tools must be used post-hoc, which limits their potential in the design of neuroadaptive systems which require real-time analysis.

Psychophysiological work, by contrast, has yielded concrete measures based on participant's physiological state. Significant relationships between a user's perceived flow and heart patterns, blood pressure and heart rate variability have been established in both learning and social media environments (De Manzano, et al., 2010; Mauri, et al., 2011). A yet more concrete relationship between electroencephalogram (EEG), electrodermal (EDA) activity, and the cognitive absorption construct has been recently discussed (Léger, et al., 2014). In this recent work, strong relationships are established between multiple exogenous variables and the perceived cognitive absorption in IT learners. These variables might likewise be applied to measure perceived cognitive load.

The Psychophysiology of Cognitive Load

Cognitive load has been measured a number of different ways since its envisioning by Sweller (1988). Much like with flow, measures have included both *direct* and *indirect* subjective measures (such as self-reports), *indirect objective measures* (such as the attainment of learning outcomes) and notably *direct objective measures* such as eye and brain tracking (Brunken, et al., 2003; Grimes, et al., 2015). Of the direct objective measures, EEG has been established as an effective tool for measuring mental workload, including in the context of cognitive load theory specifically (Anderson, et al., 2011; Murata, 2005).

Working memory is responsible for the processing and retrieval of task information. The Sweller model of CL involves the use of working memory in the acquisition of new knowledge (Sweller, 1994). Working memory is used to understand a concept, eventually abstracting the knowledge into a *schema*. More complex ideas can be acquired by further using working memory on abstracted concepts, and in this way, education is possible. However, given that working memory has limitations, too much strain on the working memory will inhibit abstraction, and in turn knowledge acquisition. We may further distinguish between *intrinsic*, *extraneous* and *germane* cognitive load (Sweller, 1998). Where intrinsic cognitive load describes the absolute difficulty of an activity, extraneous cognitive load describes the mental effort toward processing instruction. Germaine cognitive load, by contrast, describes the effort required to process schemas. From a pedagogical perspective, it is clearly desirable to be able to identify and limit extraneous cognitive load while increasing germane cognitive load.

Experiments using EEG have already identified methods for measuring cognitive load broadly. Early work in this field identified methods for measuring the demandingness of a task using EEG alpha, beta and theta waves generated by EEG and applied this to an adaptive learning system (Pope et al., 1995). Berka et al. (2004) later demonstrated how EEG could be used to identify high vigilance cognitive states by measuring the sustained differences in EEG epochs over the duration of a task. Using a wireless EEG, Berka et al. (2004) applied this technique to measuring cognitive load experienced during war simulations. Grimes et al. (2008) further refined work in cognitive load by achieving up to 75% EEG measure accuracy at classifying working memory load using just two EEG channels at Fz and Pz.

When related back to Sweller's model for learning however, we realize that these measures might be best suited to measuring the *intrinsic* cognitive load of a task, as opposed the *extraneous* or *germane* cognitive load experienced when schema formation occurs. A useful cognitive load measure for e-learning would have to account for these later two types of cognitive load so that we could correctly classify the correct circumstances under which learning occurs. How might we make this distinction?

Sweller (1998) describes extraneous cognitive load as the experience of frustration felt when concepts are demonstrated poorly. Extraneous cognitive load might be measured as the load experienced when frustrated, while germane load has no such frustration, similar to flow or cognitive absorption. However, where flow (and cognitive absorption) holds that individuals enter a state of *enjoyment* when task difficulty matches skill, germane cognitive load merely describes a state when frustration is absent. We believe that this concept of germane cognitive load better explains the phenomenology of learning. Though learning does not occur when the working memory is overloaded processing extraneous tasks, working memory is utilized in the formation of schemas. Germane cognitive load can thus be described as involving working memory utilization, low frustration, high engagement, and is positively associated with knowledge retention.

We thus hypothesize that the cognitive processes behind an online learning cognitive load model would be similar to those as cognitive absorption, but would differ on the role of *pleasure* and *frustration*. The relationship between frustration and memory load has been explored in the context of perceived ease of use by de Guinea et al. (2014), where it was found that when frustration is low, memory load has a positive effect on the perceived ease of use of a technology. Negative EEG alpha is typically thought to be generated when users are alert (Klimesch, 1999; Grimes 2008), while positive alpha is used by Léger et al. (2014) to measure the state of relaxation implicit in cognitive absorption. EEG alpha should therefore be explored to understand the impact of EEG alpha on germane cognitive load. Working memory, by contrast, as explored in neuroscience literature, establishes a relationship between working memory and EEG theta activity (Sauseng et al. 2005). We might therefore hypothesise that theta is positively correlated with online learning cognitivel load, while alpha and beta are negatively correlated. Germaine cognitive load might additionally be measured by a users' perceived absence of frustration or distraction.

Theoretical Model

Building on the work of Léger et al. (2014) we seek to use electroencephalogram to measure the frequency of EEG alpha, EEG beta and EEG theta, and correlate it with the degree of perceived cognitive load. With successful EEG measurement, we are able to specify benchmark indices for appropriate learning difficulty. Using these indices, we can measure the impact of curricula on different populations. Of particular interest to us is the impact of IT and Business learning modules on students with technical backgrounds.

The theoretical model used by Léger et al. (2014) outlines how psychophysiological factors are incorporated into the conceptual framework of the cognitive absorption construct—a model that is similar to ours. Hypotheses about the the impact of EEG, EDR, heart rate and heart rate variability were tested to understand the variance in cognitive absorption. Using these factors, the authors were able to establish the psychophysiological components of a CA model that predicts self-reported cognitive absorption. Along similar lines, we can test the relationship between EEG and germane cognitive load (GCL) for online learning, and determine whether it impacts the learning outcome. This brings us to our hypotheses and model.

- H1A – There is a negative relationship between Frustration and GCL.
- H1B – There is a positive relationship between Task Difficulty and GCL.
- H1C – There is a negative relationship between Skill and GCL.
- H1D – There is a negative relationship between Skill and Task Difficulty.

We arrive at H1A from the description of germane cognitive load in Sweller (1998). H1B, H1C and H1D were relationships observed in Léger et al. (2014).

- H2A – There is a negative relationship between activation of EEG alpha and GCL.
- H2B – There is a negative relationship between activation of EEG beta and GCL.
- H2C – There is a positive relationship between activation of EEG theta and GCL.

H2A H2B and H2C are derived from Pope et al (1995) and Berka et al. (2004), which identified EEG theta as positively associated with task load while EEG alpha and beta as negatively associated.

- H3 – There is a positive relationship between self-reported GCL and Knowledge Gained.

H3 follows from Sweller (1998), who identifies germane cognitive load as facilitating learning. We are looking specifically at *knowledge gained* as our endogenous model. It represents the difference in knowledge held before and after the lesson. Figure 1 thus summarizes our theoretical model.

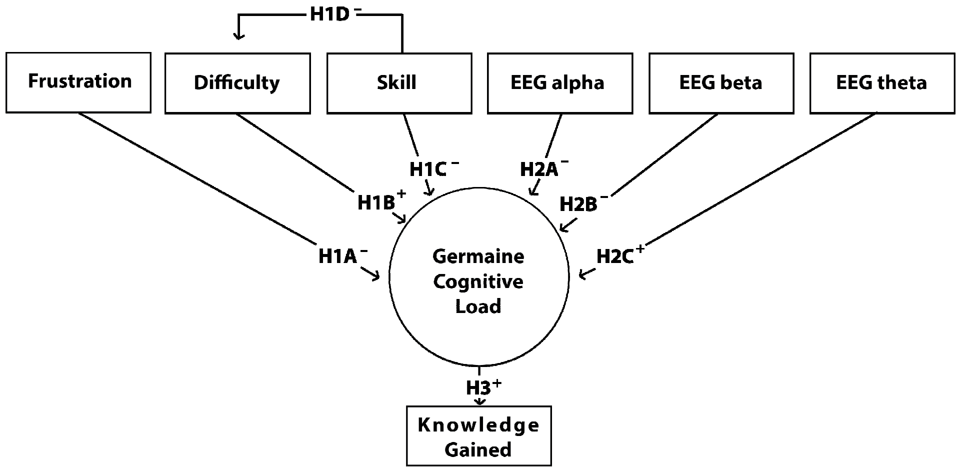

Figure 1 - Theoretical Model

Research Methodology

We will test these hypotheses by conducting an experiment using EEG to measure GCL during a learning task and by comparing between two groups of 50 subjects each with varying skill levels to manipulate the GCL. To ensure variance of the subject skill level, participants will be recruited from two separate populations of post-graduate students, MBA and Computer Science at a research intensive University. Upon arriving at the Information Interaction Laboratory, subjects will be fitted with a Muse headset—a non-invasive dry EEG designed to detect EEG alpha, EEG beta and EEG theta with electrodes on the mastoids and frontal lobe. Each subject will individually participate in two video lectures related to entrepreneurship. The two videos use the same teaching style but develop content at different paces.

Before watching each video, participants will be asked to complete a brief survey concerning their perceived knowledge of the subject. Following each video, participants are asked to complete a self-assessment questionnaire focused on their knowledge of the topic. Included in the post-questionnaire is a cognitive load instrument, consisting of a series of 27 Likert scale questions. Participants are also asked to complete a competency quiz concerning the video content, used to measure the training outcome. Data collected from the pre and post surveys are aggregated and analyzed using Partial Least Squares.

Psychophysiological Measurement using the Interaxon Muse

The Muse device generates time series EEG data from electrodes located at various sections of the head. The electrodes correspond to FpZ, AF7, Af8, TP9 and TP10 locations by 10-20 international standards (Interaxon Inc., 2015). Muse contains the libMuse library for building Muse applications, with which researchers can access alpha, beta, delta, theta and gamma EEG signals. In addition, using libMuse applications can detect blink and jaw clench events. Time-series data from the Muse sessions can thus be recorded using the muse developer recording tools and saved to a local computer. Time-series from the web interface will be recorded in browser and sent to a web database, which can be aggregated and transformed into the frequency domain if desired.

Prior studies using the Muse have found the efficacy of the device to be sound. In a joint study with McMaster University, researchers found the Muse's detection pattern to be similar to the actiCHamp and g.Tec's wet EEG system, and was used to create a machine learning algorithm that could use EEG data to predict lapses in user vigilance (Interaxon 2015; Armanfard et al 2016).

With only four channels (plus a reference electrode at FPz), the device might have limited applications in neuroscience research. In the case of cognitive load in online learning however, his should not be a challenge. Grimes et. al. (2008) demonstrated the efficacy of measuring cognitive load with only two channels. The limited number of channels comes with the advantage of cost. The Muse device was selected for the proposed experiment because of its non-invasive wireless design, low cost and compatibility with common developer tools. At $200 CAD, the device is commercially available and a magnitude less expensive than devices commonly employed in neuroscience laboratories. Unlike some of its competitors, Muse provides raw EEG data at no extra cost. By successfully demonstrating the ability measure cognitive load using the Muse, we might utilize the tool to conduct group experiments in a classroom, or to build neuroadaptive learning systems that can be affordably utilized in everyday environments.

Training Outcome

Participants will be evaluated using a multiple choice questionnaire that tests comprehension from the two modules. The results from these tests correspond to training outcomes.

Results of the EEG Technical Pilot

In order to test the efficacy of the Muse EEG and its usefulness in validating a cognitive load model, we conducted a technical pilot study. The experiment explored the use of EEG alpha and EEG beta to account for variance in self-reported flow. Given that the purpose of the technical pilot is to test the validity of our instruments and design, we opted to replicate prior work on CA, as opposed to our cognitive load model. We investigated n= 4 (2 male, 2 female) right-handed university students age range [23, 30] who were recruited from graduate management programs. The videos on MRI Safety and entrepreneurship were selected to watch, and were selected because of their pace and content differences. The objective of this pilot is to validate the technical setup and procedure using Muse EEG.

Research Instruments and Procedure

Participants watched two videos while wearing the Muse EEG. Following each video, a simple flow survey was administered. The pilot study utilized two research instruments. The first was the Muse EEG, designed to collect EG Alpha at 8-13 Hz and EEG beta at 13-30 Hz at FpZ, Af7, TP9 and TP10. These sensors follow the 10-20 international standards, which are standard wave format signals characteristically collected in Neuroscience experiments. The second instrument was a psychometric questionnaire derived from Pearce et al. (2005).

Results

With only the small sample, our preliminary results suggest a relationship between session EEG data and variance in flow. We will discuss our results, while qualifying that the objective of this technical pilot was to test the efficacy of our instruments. Though we can observe differences between EEG alpha and EEG beta and participant responses to the questions, we can visualize the differences by focusing on a subset of our scale derived from Pearce et al. (2005). This simple scale measures Flow by focusing on two dimensions: self-described “challenge” and “skill”. Figure 2 depicts the average (normalized) relative EEG alpha and EEG beta from the TP 9 and TP 10 electrodes and the Pearce Flow measure, calculated by aggregating participant responses to the “difficulty” and “skill level” questions.

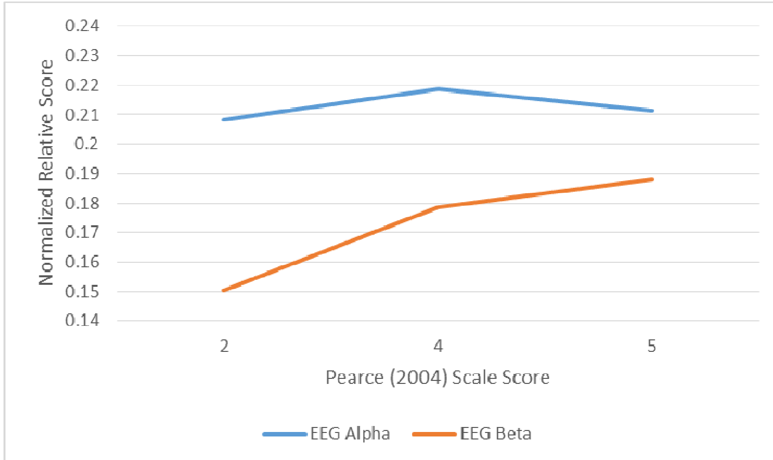

Figure 2 Normalized EEG Readings in TP9 and TP10 by Self-Reported Flow

These results are interesting. A score of 4 denotes an appropriate match between task difficulty and skill. The average EEG alpha was higher when the task was appropriate in challenge and skill dimensions, while EEG beta was lower when these dimensions were low. Though the device might be too noisy for detailed research in event-related potentials, the consistency suggests that the Muse might be suitable for research in social science which relies on the presence of the EEG alpha and beta waves. Given the device's low cost, it may be adequate for the experimental development of neuroadaptive learning tools.

Pilot Study Limitations

The small sample size is certainly a limitation of our findings. Though the experiments produced a multidimensional dataset, the number of experimental instances inhibits thorough statistical analysis. Under these circumstances, statistical analysis or machine learning at best demonstrate the potential for analysis on a larger sample. In addition, the ability to reproduce results concerning cognitive absorption does not validate the degree of accuracy of the Muse EEG system, but it does demonstrate its efficacy. Given that thorough research has been conducted on the device comparing it to other EEG, we can proceed with deeper exploration in online learning. The second stage of this exploration could involve further validating the Muse EEG alpha and beta with the actiCap by having participants wear both devices simultaneously as they perform e-learning tasks. Future research will also include larger participant sample sizes as well as different e-learning content to evoke high and low levels of germane cognitive load in subjects.

Discussion and Conclusion

The main advantage of using the Muse EEG is that it is non-invasive and can connect to most computers using Bluetooth. Where other EEG technologies offer comprehensive electrode locations, they use messy saline solutions or gel. Though they produce high-quality data, they are prohibitive for use in conventional business computer laboratories or e-learning environments. Muse, by contrast, records data from most of the important scalp locations for our task at the presumed expense of data quality. The non-invasive nature of the Muse adds the advantage of being able to measure the impact of brain activity on e-learning in an environment similar to where the modules would normally be delivered. The tool's low cost also opens the possibility of measuring the impact of group interaction or social modules, which would normally be prohibitive by the high cost of the standard research EEG. Validating the robustness of this tool is thus critical to future research endeavors.

Business students and technical students think in very different ways, and have different exposure to technical or business content. Given the wide variance in skill between the groups, we expect our future experiments will allow insights into the role of cognitive load on learning outcomes to aid in the development of online learning benchmarks, which can be useful for determining whether a module is too difficult or not sufficiently engaging. By exploring the differences in psychophysiological performance between the two groups, we can gain insight into the mechanisms indicative of experiencing optimal cognitive load and cognitive absorption. Moving forward, this experiment might be advanced to develop e-learning modules that utilize the model to build real-time adaptive learning systems that transform the instructional design through the use of EEG feedback.

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